Automated CT-based THA planning for optimizing joint functionalities: a "maximum a posterior" (MAP) estimation approach

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Introduction: Total hip arthroplasty (THA) is one of the most suitable application targets of the CAOS technologies. While intraoperative computer and robotic assistance for THA has been intensively studied in the past decade, less attention has been paid to preoperative planning. We recently developed automated preoperative planning systems for single implants for THA, that is, the femoral stem and acetabular cup, based on statistical models of bone-implant spatial relations constructed from a number of 3D datasets of past THA plans (which we call "training datasets" hereafter.) [1, 2]. However, the optimal THA plans should incorporate joint functionalities, which are evaluated based on not only spatial statistics between the single implant and its host bone but also physical parameters such as ranges of motion (ROMs) and limb length difference (LLD) determined by multiple implants.

In this paper, we describe a method for automated THA planning incorporating joint functionalities. The optimal planning is formulated as maximum a posterior (MAP) estimation, which ensures the best-balance of joint functionalities and bone-implant spatial relations based on their statistical models derived from the training datasets.

Methods: We assume that the pelvis and femur shapes reconstructed from patient 3D CT data are given as input datasets.

MAP formulation of our previous method for single-implant planning: In our previous work [2], the statistical shape model (SSM) of combined shapes of the pelvis and implanted acetabular cup was constructed from the training datasets of the cup plan. Let X and Y be pelvis and cup shape parameters represented in SSM, respectively. The cup size, position, and orientation are implicitly embedded in the cup shape parameters Y. The SSM defines prior probability P(X, Y) modeled by Gaussian distribution whose covariance matrix is obtained by principal component analysis. Least squares criterion for fitting the patient pelvis shape data D to the pelvis part X of the SSM amounts to modeling the conditional probability P(D|X) as Gaussian distribution. In our previous work, we obtained cup shape parameters Y maximizing P(X, Y) P(D|X) which is equivalent to maximizing the posterior probability P(X, Y|D) based on the Bayes' rule. (Note that P(X, Y) P(D|X) amounts to P(X, Y) P(D|X, Y) because D depends only on X.)

Extending the MAP formulation to incorporate joint functionalities: The joint functionalities are related to both the acetabular cup and femoral stem. In this study, we assume that the stem plan is determined only using the femur-stem statistical model described in our previous work [1] because automated stem planning is sufficiently stable by itself.

Let Z be joint functionality parameters and P(Z) be their prior probability distributions. We formulate the automated planning incorporating joint functionalities as finding cup parameters Y maximizing the posterior probability P(X, Y, Z|D), which is equivalent to maximizing P(Z) P(X, Y) P(D|X), in which P(X, Y) P(D|X) described in the previous subsection is multiplied by P(Z).

Now, the problem is how to model P(Z) for each functionality parameter from the training datasets. High probability values in P(Z) should mean high functionality as well as frequent occurrence. In order to derive a suitable model of P(Z), we assume that experienced surgeons aim at recovery of the highest functionalities in the best-balanced manner. This means that higher functionality should have occurred more frequently in the training datasets. In order to represent the above assumption, we model P(Z) as Gaussian distribution whose average represents the highest functionality (for example, 0 mm for LLD and $+\infty$ for ROM). The distribution (histogram) of each raw functionality parameter (e.g. ROM) obtained from the training datasets is converted to normalized (half-) Gaussian N(0, 1) by a variable transformation technique so that the highest functionality parameter value is mapped to zero in the transformed variable. This variable transformation also normalizes different functionality parameters so as to realize the best balances embedded in the training datasets. Therefore, P(Z) is modeled as Gaussian distribution having the unit convariance matrix, where Z is the transformed variables of raw functionality parameters.

Results: We used 37 datasets of past THA plans as the training datasets, and leave-one-out cross validation was performed. As the input datasets, we used manually segmented pelvis and femur shapes from CT data. We incorporated the cup coverage ratio as well as ROM and LLD as joint functionality parameter. One pattern of ROM (internal rotation at 90-degree flexion) was considered. Figure 1 shows a typical case of automatically generated THA plans. In this case, ROM and LLD were largely improved in the proposed method in comparison with the previous method. Further, all the three functionality parameters were slightly better than surgeon's plan.

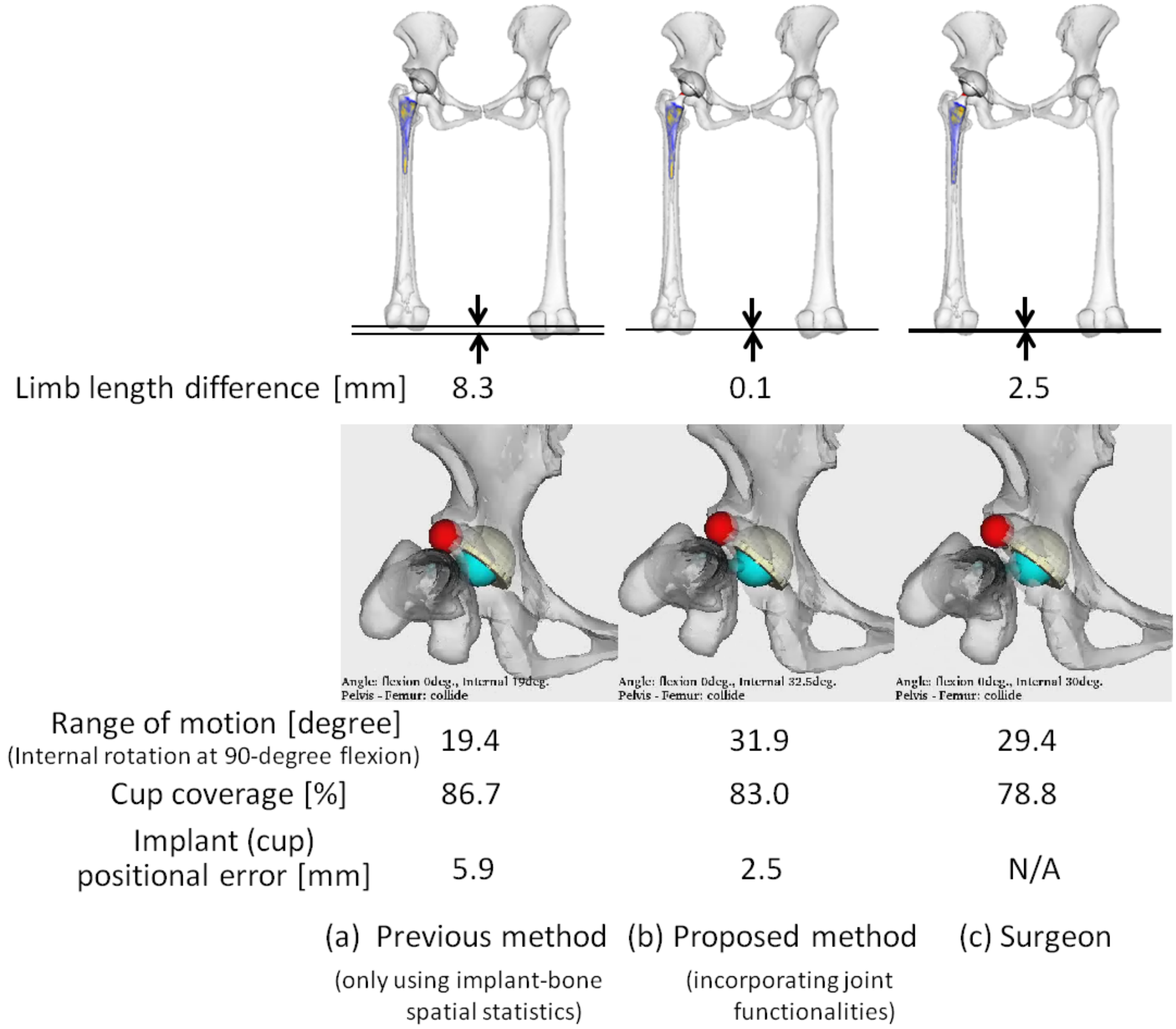

Fig. 1: Typical case of automated THA planning.

The average of LLD of 37 cases was 5.21 mm, 2.18 mm, and 3.13 mm in the previous and proposed methods, and surgeon's plan, respectively. 46.8 deg, 48.5 deg, and 46.5 deg for ROM, and 81.1%, 84.5%, and 82.4% for cup coverage. Statistical significance between the proposed and previous methods was confirmed in LLD ($p<0.01$) and cup coverage ($p<0.01$), while no significance between the proposed method and surgeon's plans in all three functionalities.

Discussion & Conclusion: We have described MAP formulation of automated THA planning incorporating joint functionalities. The method fully utilizes the training datasets of past 3D THA plans to construct statistical models of the bone-implant spatial relations and joint functionalities. The objective function, that is, the posterior probability in the MAP formulation, was automatically generated from the training datasets. By incorporating the statistical model of the functionalities, two of the three functionalities were significantly improved compared with the previous method.

In this paper, we used manual segmentation as input bone 3D shape datasets. However, we have already developed automated CT segmentation software and showed that clinically acceptable accuracy was attainable [3]. Thus, we will start experiments using automatically segmented 3D shapes.

References

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